Dynamic predictive reliability assessment of ship systems

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Abstract

Recent research shows that maritime industry has adopted innovative and sophisticated inspection and maintenance practices. A flexible framework, applicable on complex machinery, is introduced towards ship maintenance. A holistic inspection and maintenance notion is implemented, introducing different strategies, methodologies, and tools, suitably selected, for each required ship system. The proposed framework enables predictive reliability assessment of ship machinery, while scheduling maintenance actions by enhancing safety and systems' availability. This paper presents the Probabilistic Machinery Reliability Assessment (PMRA) strategy, which achieves predictive reliability assessment and evaluation of different complex ship systems. The assessment takes place on system, subsystem and component level, while allowing data fusion of different data types from various input sources. In this respect, the combination of data mining method (k-means), manufacturers' alarm levels, dynamic state modelling (Markov Chains), probabilistic predictive reliability assessment (Dynamic Bayesian Belief Networks) and qualitative decision making (Failure Modes and Effects Analysis) is suggested. PMRA has been clearly demonstrated in a case study on selected ship machinery. The results identify the most unreliability systems, subsystems and components, while advising practical maintenance activities. The proposed PMRA strategy is also tested in a flexible sensitivity

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analysis scheme.

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1. Introduction

Machinery failures in the day-to-day ship operations may lead to major accidents, endangering crew and passengers onboard, posing a threat to the environment, damaging the ship itself and having a great impact in terms of business losses. As stated by Hunt and Butman (1995), making decisions under conditions of risk and uncertainty has always been the shipowners' challenge Soares and Teixeira (2001). Expanding this statement, the authors' belief is that risk and uncertainty control as well as safety awareness is responsibility of all involved maritime stakeholders contributing actively towards safety enhancement. As a matter of fact, the development and establishment of safety regulatory frameworks in the maritime industry is led by lessons learnt from hazardous incidents and accidents. Several marine and offshore casualties took place in the last decades such as Titanic (1912), Derbyshire (1980), Herald of Free Enterprise (1987), Piper Alpha (1988), Exxon Valdez (1989), Scandinavian Star (1991), Estonia (1994), Petrobras P-36 (2001), Star Princess (2006), Deepwater Horizon (2010), Costa Concordia (2012), among others.

The most recent casualty statistics for the period 2000-2014, published IUMI Facts and Figures Committee (2015), present that the causes leading towards total (entire vessel) or serious losses (particular systems or structural members) are listed as weather, grounding, fire/explosion, collision/contact, hull damage and machinery failure. The dominant causes triggering serious losses are recorded among machinery damage, grounding and collision/contact. Especially, machinery failure reports over 35% of all losses for the period. Hence, more than one third of the losses caused due to machinery failure. Furthermore, recent research shows that competition in maritime market develops more compound and pretentious structure affected by parameters as time, economical restraints, technology and innovation, quality, reliability and information management. In relation to successful business competence, strategic planning should be enhanced considering assets availability, involving maintenance and reliability operational aspects. The latest technology controlling these parameters is focused on holistically monitoring the condition of main and auxiliary machinery.

Before exploring the latest literature review, it is crucial to identify the functionality of maintenance. In this respect, several definitions are provided by various authors, summarising that maintenance is a set of technical, administrative and managerial actions targeting to retain or restore the state of a system to function as required Dikis et al. (2014). Moreover, parameters such as reliability, availability, risk of failure, uncertainty and machinery downtime also affect operational expenses. Hence, nowadays maintenance is encountered as an operational method, which can be employed both as a profit generating process and a cost reduction budget centre through an enhanced Operation and Maintenance (O&M) strategy. Inspection and maintenance activities have been reformed from reactive to proactive. Therefore, the notions of failure prevention and risk control are introduced. Specifically in shipping industry, where vessel's availability and accessibility are vital. This maintenance reformation is achieved through transition of maintenance strategies from corrective to preventive and the most recent predictive strategy.

This paper presents the development of PMRA strategy for ship machinery and equipment, which integrates various processes for data mining, dynamic state modelling, reliability assessment and fundamental aspects of decision making. Overall, the main aim of this research work is to tackle the issue of optimal ship machinery maintenance strategy by establishing a novel dynamic, predictive, probabilistic reliability assessment strategy. More analytically, this research achieved to integrate the data mining method of k-means for information extraction, manufacturer alarm levels, dynamic state modelling utilising Markov Chains (MC), probabilistic predictive assessment of risk employing Dynamic Bayesian Belief Networks (DBBNs) and qualitative decision-making of

Failure Modes and Effects Analysis (FMEA).

PMRA strategy encompasses the benefits of qualitative and quantitative assessment. The core innovative feature of PMRA strategy is oriented towards the utilisation of raw data collected in actual sailing conditions, components' failure interaction and state interdependencies, which provide holistic view of systems' reliability performance. Lastly, a detailed sensitivity assessment scheme examines the accuracy and modelling flexibility of the suggested PMRA strategy.

2. Literature review

In this section, the literature review is demonstrated incorporating recent research background considerations and tendencies. The research topic is oriented towards the latest inspection and maintenance methodologies such as Condition Based Maintenance (CBM), Computerised Maintenance Management System (CMMS) and Asset Management (AM). Furthermore, different condition monitoring technologies will be presented and the latest on-condition assessment functionalities. This critical literature review refers to efforts demonstrating the evolution and reformation of maintenance from corrective to preventive and then to latest predictive strategy. The latest strategy is the predictive, which has been introduced into market between 1960s and 1970s Shreve (2003) Arunraj and Maiti (2007). The maintenance strategy notion is characterised by the non-destructive reactive mode of testing a system, determining the condition of equipment and subsequently considering the maintenance plan.

2.1. Condition Based Maintenance (CBM)

The most recent methodology offering control of risk and uncertainty is known as Condition Based Maintenance (CBM) Goossens and Basten (2015). The fundamental idea of this framework is the on-condition assessment of systems and machinery by considering specified record measurements that will potentially lead to risk or reliability state identification. This state identification is separated into two major areas of on-condition assessment the diagnostics and prognostics. In the first place, diagnostics allow the identification of occurred failure modes, whereas, in the second case prognostics aim to forecast the future risk performance.

The scope of CBM and fault diagnosis as defined by Mechefske (2005) is to detect the upcoming failure before even incipient failures take place, aiming to enhance machinerys availability, reliability, efficiency and safety, by reducing maintenance costs through controlled spare part inventories. A survey Prajapati et al. (2012) on CBM applications highlights the key aspects as data collection, artificial intelligence, and statistics allow intelligent maintenance and prediction of consequences using past and current data.

In the industrial domain, SKF, a leading global product, services and technology provider, supports that CBM aims to identify risks and predetermination of strategic actions SKF (2012). Hence, implementation of CBM should lead to reliability enhancement and cost reduction by integrating information and management of critical components for time reduction of expensive and challenging maintenance phases such as dry-docking. In order to layout CBM and the processes that consists of; Tsang et al. (2006) suggest a data structure leading to decision analysis according to machinery's condition, proposing a method for data-driven CBM achieving data preparation, model assessment, decision-making and sensitivity analysis. Similar condition monitoring modelling structure has been introduced in the suggested PMRA strategy and will be presented in the methodology section next.

2.2. Computerised Maintenance Management System (CMMS)

As equipment onboard the ships becomes more complex and the market gets more competitive, the need for implementation of automated maintenance management systems is presented. Computerised Maintenance Management Systems (CMMS) is the latest framework which allows machinery and equipment functionality, reliability and availability enhancement and uncertainty control by employing computerised, flexible tools for managing critical assets.

According to Shreve (2003), CMMS suggests maintenance planning as it assists using critical data for equipment, workforce and recorded conditions. Fernandez et al. (2003) present the functionality of CMMS in order to gain information from raw data and enhance decision-making by automating existing iterative assessment processes. On the other hand, Monostori et al. (2006) state by summarising mobile solutions for maintenance applications that CMMS employs continuous connectivity including active data management, web-based interaction, access to knowledge and information and enhancement of communication systems.

In contrast, Chryssolouris et al. (2004) explore the difficulties arising from the integration of partners' heterogeneous/incompatible IT systems on ship repair industry by presenting a solution for connectivity of various modern IT systems. As stated by Sherwin (2000), maintenance has to be considered as key factor within the business as changes in its processes affect various interrelated functions. Lastly originated from this view, Kans and Ingwald (2008) present the benefits of an integrated database and the significant role of maintenance performance in economic improvement.

2.3. Asset Management (AM)

An innovative and widely applicable methodology spread over in the maintenance evolution is Asset Management (AM). This practice targets the business oriented implementation by concentrating on the overall asset performance. AM is extensively assessed and introduced into multiple industries and nowadays successfully in maritime by leading machinery and equipment manufacturers. AM integrates notions, tools and features from risk based assessment methods, CBM and CMMS as already presented.

Through a critical review focusing on the cost benefits of maintenance strategies and methodologies, Eti et al. (2006) summarises that maintenance and AM can achieve growth of operational profile by decreasing running costs and increasing capability and availability. ABB is a global leader in power and automation technologies ABB (2010) proposing the basis of an ultimate AM tool integrating CMMS with real-time CM, which collects data from various sources and alerts on failure detection. Furthermore, Asset Health Centre (AHC) is presented by ABB as well ABB (2012). AHC performs as an entire business asset supervision system utilising reliability, performance, prioritising maintenance actions, and minimising Operations and Maintenance (O&M) expenditures. AHC's innovation is the integration of Operation Technology (OT) and Information Technology (IT) by enhancing decision-making on asset's existing condition.

2.4. Condition monitoring technologies

As already defined, CBM is the latest maintenance methodology, which assesses systems' and machinery risk of failure performance, while functioning. In this case, CM introduces technologies and tools that are employed for the on-condition assessment. CM technology is applied through various tools, recording and evaluating measurable parameters that will be reviewed in this section. These measured parameters comprise the signal gathering, from which several data processing methods can be considered with respect to machinery recorded input data. Precisely, K. (2012) defines health assessment as method measuring wear and system performance.

CM is identified by Delvecchio (2012) in steps such as data acquisition, signal processing and feature extraction, signal analysis and fault detection, leading to decision-making and failure prognostics. Moreover, Jiang and Yan (2008) present the most popular CM tools as lubrication oil testing, vibration and Acoustic Emissions (AE) among others. Additional CM technologies and methods list thermography, ultrasonic monitoring and the traditional visual inspection.

More specifically, vibration monitoring is the most known and well-applied technique. Vibration-Based Maintenance (VBM) methodology offers early indication of machinery malfunctions involving parameters as rotational speed, loading frequency, and material state AlNajjar (1996). These parameters can be measured and evaluated by employing different data gathering equipment (sensors) such as displacement, velocity and acceleration sensors.

On the other hand, thermography is a technique, applicable to both electrical and mechanical equipment, and is deployed to identify hot and cold spots providing early signs of equipment failure. As claimed by Bagavathiappan et al. (2013), Infrared Thermography (IRT) is one of the most accepted CM tools. Due to the non-contact function is suitable for detecting structural, machinery, electrical and material malfunctions. The key advantage of IRT compared to other CM tools is the real-time representation of pseudo colour coded image.

Oil analysis is achieved through laboratory concentration investigation in lubricant, known as debris analysis, which deals with shape, size, composition of wear particles and lubricant degradation analysis for physical and chemical characteristics Jiang and Yan (2008). Lubricants' monitoring seems to be the most efficient diagnostic tool as from a small amount of fluids the condition of the entire lubricant in each machinery can be determined.

The applicability and efficiency of ultrasonic condition monitoring is confirmed by International Association of Classification Societies (IACS) as this technique is authorised from Classification Societies for surveys and certifications. Specifically, acoustic and ultrasonic monitoring is utilised in the well-known Ultrasonic Thickness Measurements (UTM) IACS (2004), IACS (2006). In practice, Kim and Lee (2009) propose a real-time diagnostic system for high speed Acoustic Emission (AE) signal analysis assessing wear condition of cylinder liners in marine large two-stroke diesel engines.

2.5. Condition monitoring functionalities

On-condition assessment targets to evaluate the state of degraded ship systems and machinery. In this section, two functionalities of CM will be evaluated the diagnostics and prognostics.

As already defined, CM is the technology of assessing the state of machinery without interrupting the operation. In line with Delvecchio (2012), fault diagnosis is severe requiring the determination of type, size, location and time of detected faults. Supporting the importance of accurate and early fault diagnosis, Refocus (2005) states that a specific maintenance issue can be the replacement of a \$5,000 bearing turning into a \$220,000 project concerning cranes, service crew and power loss.

An innovative and newly introduced maintenance concept on CM technology expansion of diagnostics is the prognostics. This notion scopes to predict, whether a failure will occur by considering the Remaining Useful Life (RUL) of systems. As defined by Lee et al. (2014), Prognostics and Health Management (PHM) combines health condition and RUL prediction for an overall system and its associated components. On-condition assessment of systems typically use fault detection and diagnostic technologies, which extend from single threshold to rule-based algorithms Byington et al. (2002). Additional prognostic approaches involve experienced-based modelling and physics-based also known as first principle analysis prognostics. It is crucial to highlight that prognostics offer limited literature, as they are recently established.

A methodology predicting the RUL of natural gas export compressor is proposed by Nystad and Rasmussen (2010) integrating Technical Condition Index (TCI) parameters, historical data with PHM and the general maximum-possibility theory. The requirement for an improved prognostic CM maintenance concept develops the multi-component modelling. This notion incorporates the risk assessment of different components of a system by allowing an overall performance monitoring compared to independent evaluation. Therefore, Liu et al. (2012) expand the prediction concept by proposing an innovative data-fusion prognostic framework. This concept improves the accuracy of long-term condition forecasting by combining the advantages of data-driven prognostic method and the model-based particle filtering approach in system state prediction. The data-fusion concept has been incorporated and contributing segnificantly in the PMRA strategy development, which will be presented next.

3. Methodology

According to the latest critical literature review, the present research contribution is focused towards the establishment of an efficient maintenance strategy for systems and machinery. This strategy fulfils requirements such as:

- Scalable and adaptable structure of maintenance strategy facilitating multiple ship systems
- Integration of CM aspects incorporating performance assessment, predictive reliability analysis, and degradation drop
- Essential CM prognostic features involving raw data analytics and feature extraction utilising novel data mining methods
- Risk and reliability assessment targeting root cause analysis of failures
- Consideration of system, subsystem and component operational dependence as degradation or failure of one can lead to failure of multiple others (i.e. failure interaction)

3.1. PMRA strategy framework

It is essential to highlight that the proposed PMRA strategy has been formed as framework. Therefore, PMRA strategy enables predictive reliability assessment utilising processed (by external data providers such as databases)or raw data. The overall PMRA strategy framework consists of four stages such as the data collection, data processing, predictive reliability assessment and decision making as shown in Figure. 1. This paper's methodology and involved case study will implement only raw data, because this data type demonstrates analytically the innovation of the suggested strategy and incorporates all involved data processing methods and tools.

STAGE 1: Data collection. This stage refers to data gathering from input sources such as sensors, which provide raw data (i.e. performance measurements of temperature and pressure) or databases and particular shipping stakeholders (i.e. service providers, ship owners and operators, Classification Societies etc.) for providing processed data. The proposed PMRA can be adapted to utilise processed input or raw data as it is described in the following stage. Overall,

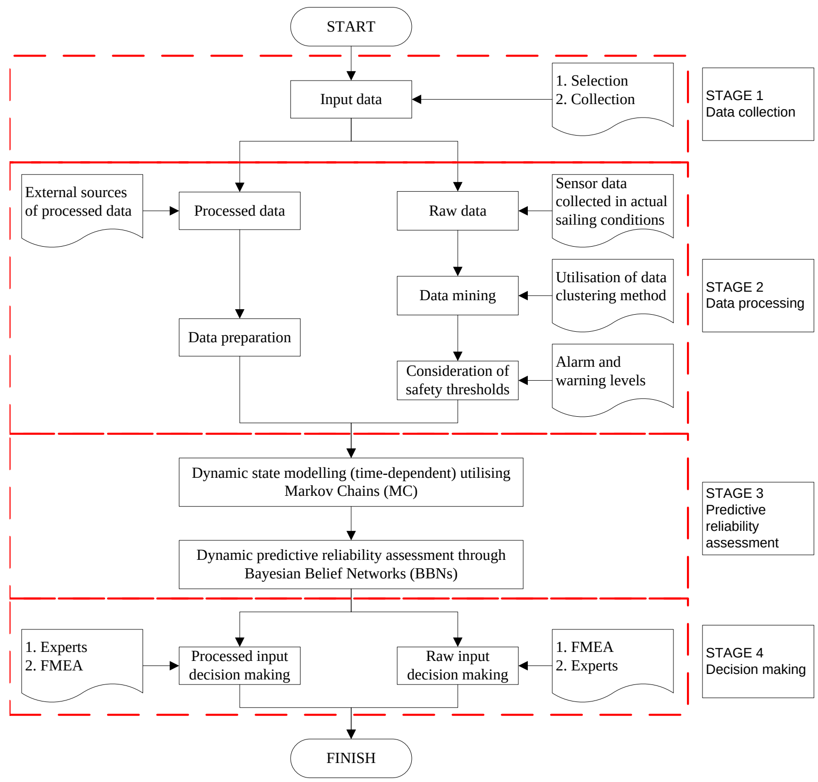

Figure 1: PMRA strategy flowdiagram

PMRA strategy merges historical data, expert judgement, and raw/real-time sensor data. The historical input includes information such as inspection and maintenance actions and intervals as well as manufacturers manuals for practical information extraction, which is relevant for the decision-making. Expert judgement involves failures and related measures including consequences, technical and economic impact sources by Classification Societies reports, inspection findings by crew-members, ship operators and superintendents. Historical data and expert judgement information are supplementary in CM methods providing technical input on decision-making activities as described in Stage 4. On the other hand, the third and critical data group is the raw/real-time monitoring data type corresponding to on-board measurements and records gathered, while the vessel operates. Parameters that can be recorded on-board the vessel vary including operational parameters per trip, ship sailing condition parameters, environmental parameters, and ship machinery performance measurements. This paper is focused towards these parameters consisting of temperature and pressure in various locations on the critical machinery of the ship.

STAGE 2: Data processing. The second stage of PMRA strategy framework takes into account data processing techniques. These differ between the processed and the sensor/raw data. The first data type has been already processed by external stakeholders, which provide data such as failure rates. Therefore, these failure rates, in percentage, form the input of the following Stage 3 "Predictive reliability assessment".

On the other hand, sensor data is considered as raw. Therefore, PMRA strategy incorporates innovative selected data mining methods extracting hidden information from the recorded datasets and transform it into useful and understandable structure for further elaboration. In other words, data mining is the practice of investigating patterns such as similarities and differences in collected data. Literature presents a wide range of data mining methods such as classification, regression, clustering, summarisation, dependency modelling and change and deviation detection Dikis et al. (2017).

Two well-known algorithms are the k-means and EM algorithm. They share common aspects such as the iterative clustering procedure of guessing parameters targeting convergence according to predefined criteria. However, the main differences among k-means and EM algorithm are related to the clustering practice and the calculation of the distances. Firstly, k-means employs hard clustering, whereas, EM soft. Furthermore, k-means method implements the Euclidean distance while calculating the distance between items, whereas, EM utilises statistical methods Dikis et al. (2017). On the other hand, EM algorithm assigns the points in the clusters, when convergence is reached, whereas, k-means reallocates them at each point until convergence Hand et al. (2001). A comparative research study between k-means and EM algorithm performed by Jung et al. (2014) shows that k-means provides more accurate data clustering, especially when the number of clusters is small Williams and Simoff (2006), whereas, EM algorithm is faster in processing. Therefore, PMRA strategy will involve two clusters in order to benefit this efficiency. One cluster groups the observations, which have value smaller than the mean value of the recorded dataset and the second groups the higher. This clustering approach enables to identify the tendency of inclination from the mean value of the recorded dataset by allocating observations in two clusters.

Due to accuracy, efficiency, simplicity and flexibility, k-means method will be utilised by the PMRA strategy in order to partition the recorded observations provided by the on-board sensors. Summarising, k-means algorithm offers the advantages that will benefit the raw sensor data processing of PMRA strategy MacQueen et al. (1967), Jain et al. (1999). First of all k-means is unsupervised data mining method, that does not require supplementary input data for training and classification, hence it is suitable for limited available input data. Furthermore, it is partitional method employed in engineering practices, where single partitions are required. K-mean is determined as hard data clustering method (not overlapping) simplifying calculation processes as each observation belongs to one cluster or not. Additionally, k-means method is suitable for excessive data quantity (if available) as it is easily programmed and computational efficient, when number of clusters is small.

The method of k-means partitioning belongs to square error, partitional data clustering. This method separates data into clusters creating strong association among members of the same cluster and weak between different clusters Gerardo et al. (2005). The data clustering method of k-means has a structured iterative process, which requires the following Gerardo et al. (2005), Williams and Simoff (2006):

- Identify number of k clusters
- Initiate the calculation of means from μ_1 until μ_k of k clusters
- Generate random selection of objects

- Assign each pattern to the closest cluster centre. If the data point is closest to its own cluster centroid, proceed to the following data point. If not, move it into the closest cluster

- Calculate minimum Euclidean distance determining the membership for the respective clusters

- Determine the membership and assign each point to corresponding cluster

- Iterate until the criterion function converges. During iteration process recalculation of μ_1-μ_k is taken place until there is no change in the value of mean

K-means method identifies the recorded dataset pattern (i.e. increase or decrease) and specifies the distance of the calculated centroids from the specified alarm levels. This distance is expressed in percentage and defines the healthiness of the recorded data. Therefore, the data transformation stage utilised the results of k-means data clustering method and employs predefined alarm limits. These limits classify the recorded input data among acceptable and abnormal functioning levels. In maritime industry, alarm limits can be assigned by various stakeholders and experts such as ship machinery and equipment manufacturers, ship owners, operators and service providers as well as Classification Societies. The alarm limits are utilised as reference points comparing the recorded, predicted and warn levels.

Technical input for identifying alarm levels requires expert judgement and subjective decision-making. Hence, establishment of safety thresholds from these stakeholders may lead to technical assumptions. Therefore, in the case of PMRA, the alarm levels are identified through the machinery manufacturers manual and the optimal operating condition by the sea trials reports. These records fulfil the manufacturers requirements, whereas the sea trials provide the ideal available reference points for the required comparison, because the machinery on the vessel is tested in brand new condition.

$$P_{ds}(w_t) = \frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j} c_i^j < l}{m_j} \times 100 \tag{1}$$

$$P_{ds}(f_t) = \frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j} c_i^j \geq l}{m_j} \times 100 \tag{2}$$

Equation 1 presents the probability of working state (occurrence of acceptable indices/measurements) for data set ds at t time-frame $P_{ds}(w_t)$ in case of upper threshold limit selection such as temperature measurements. On the other hand, equation 2 demonstrates the probability of failing state (occurrence of measurements exceeding the limits). In these mathematical expressions, c_i^j denotes the clustered input data point, result of k-means, l represents the predefined limits (i.e. safety thresholds) and m_j the entire number of clustered indices.

$$P_{ds}(w_t) = \frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j} c_i^j > l}{m_j} \times 100 \tag{3}$$

$$P_{ds}(f_t) = \frac{\sum_{j=1}^{k}\sum_{i=1}^{m_j} c_i^j \leq l}{m_j} \times 100 \tag{4}$$

In a similar manner, equations 3 and 4 present the probability of working and failing states respectively, in the case of lower threshold selection such as pressure measurements, considering the relations with the selected limits l.

STAGE 3: Predictive reliability assessment. This stage of PMRA framework is the predictive reliability assessment, which consists of two main models. The first one deals with the dynamic state modelling, hence the time-dependencies, whereas the second with the reliability assessment. Both models are integrated establishing the dynamic predictive reliability assessment tool of PMRA framework. Having in mind as fundamental notion that systems functioning degrade, PMRA examines different states of reliability drop within the assessed time-line.

A well-known process, established by Andrey Markov, is the Markov Chain (MC) or Discrete-Time Markov chain (DTMC) Norris (1998), which examines the state variation into a discretised time-line. According to Ghahramani (2001), MC model is tool for representing probability distributions over sequences of recorded data points denoting the observation at time t and the variable Y_t. PMRA strategy employs the mathematical tool of first-order Markov Chains (MC) Yan et al. (2011), Fort et al. (2015). First-order MC is mathematical system that undergoes transitions from one state to another within the state space Dikis et al. (2015).. Furthermore, MC is selected, as it is flexible to set up by allowing different levels of state sequence complexity.

First-order MC process connects the results acquired by k-means data clustering method and the implementation of alarm levels with the following dynamic reliability assessment tool. Therefore, k-means clustering and alarm levels specify the normality of the recorded dataset, by transforming it into percentage, demonstrating the distance from the defined alarm levels. These values are fed into the MC process generating the state transitions within the time-line. Hence, MC outcomes provide the relevant sequence of connecting the past values with the present and the present with the predicted.

$$P(X_{n+1} = x|X_n = y) = P(X_n = x|X_{n-1} = y) \tag{5}$$

In MC sequential arrangement of random variables $X = (X_1, X_2, ..., X_n)$ a joint distribution is specified by the conditionals $P(X_i|X_{i-1}, X_{i-2}, ..., X_1)$ Fosler-Lussier (1998). As Markov property states in the simplest form of MC, the dependency of current variable is associated explicitly only to previous variable. This is the first-order MC model arrangement as shown in equations 6 and 7.

$$P(X_i|X_{i-1}, X_{i-2}, ..., X_1) = P(X_i|X_{i-1}) \tag{6}$$

$$P(X_0 = x_0, ..., X_n = x_n) = P(X_0 = x_0) \prod_{t=1}^{n} P(X_t = x_t|X_{t-1} = x_{t-1}, ..., X_0 = x_0) \tag{7}$$

Therefore, a generalised form of MC of order m (m stands for memory), is process satisfying:

$$P(X_n = x_n | X_{n-1} = xn-1, X_{n-2} = x_{n-2}, ..., X_1 = x_1) = \\ P(X_n = x_n | X_{n-1} = x_{n-1}, X_{n-2} = x_{n-2}, ...X_{n-m} = x_{n-m}) \quad (8)$$

for $n > m$

On the other hand, the reliability assessment stage employs the results of MC in order to identify all probable failure case scenarios. This particular stage employs the dynamic state modelling aspects (time-dependencies) and reliability assessment through the appropriate network arrangement. The predictive reliability assessment stage is common in structure, and functionality for both processed and raw data (Stage 1: Data Collection). The scope of this processing stage is to obtain the predicted reliability states on system, subsystem and component.

The reliability assessment involves the quantitative risk tool of Bayesian Belief Networks (BBNs). BBN is represented as a Direct Acyclic Graph (DAG), which consists of nodes (variables) showing the different system's, subsystem's and component's states and a given set of arrows (edges), which represent the probabilistic dependence among the variables and interconnect the nodes. The main advantage of BBNs is the flexible network arrangement allowing to adapt on the system's requirements on size, shape and connections (edges).

This key feature of DBBNs is significant and innovative, compared to the remaining quantitative risk and reliability methods (i.e. fault tree analysis and event tree analysis), as it allows the simulation of functions and operations on actual modelling environment. The DBBN is defined as probabilistic graphical model involving conditional dependencies arranged into Directed Acyclic Graphs (DAG) and it is expressed as presented in Dikis et al. (2015).

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (9)$$

Where P(A) and P(B) are the probabilities of events A and B, while A given B and B given A are conditional probabilities (as shown in equation 9).

Each system, subsystem and component, hence each node such as parent or child (not root nodes), is linked with a certain number of events or failure modes that varies per node. Therefore, multiple probabilistic failure case scenarios are formed among the associated nodes. Assuming that a child node has k parent nodes receiving input from, the generated number of probabilistic failure case scenarios is expressed as $m = 2^k$.

From fundamental probability theory, the joint probability per node, involving random variables such as W, X, Y, and Z, is known as the product of conditional probabilities shown in 10.

$$P(W, X, Y, Z) = P(W)P(X|W)P(Y|W, X)P(Z|W, X, Y) \tag{10}$$

STAGE 4: Decision making. This is the last stage of the PMRA strategy framework. Decision-making requires input from Stages 1 and 3 "Data collection" and "Predictive reliability assessment" respectively. As part of the last stage of PMRA strategy, decision-making offers practical inspection and maintenance action suggestions, sourced by the first stage of this framework. On the other hand, decision-making takes into account the past, current and predicted reliability performance as acquired by the previous processing stage. This stage examines the root cause of failures or abnormal functioning and provides practical solutions. Overall, decision-making offers practical suggestions, hence, it has been developed into a qualitative manner. This last stage incorporates expert judgement of ship owners, service providers, Classification Societies, chief crew members and chartered engineers gathered as part of this research. Additionally, Original Equipment Manufacturers' (OEMs) manuals and reports provide valuable contribution.

A qualitative risk assessment tool known as Failure Modes and Effects Analysis (FMEA) has been introduced in guiding the user for identification of failure modes, effects, damaged equipment and components and appropriate failure causes. The FMEA takes into account the under investigation ship subsystem, the gathered measurement, parameter, potential failure mode, effect of failure, damaged equipment and component and the malfunction/failure cause.

PMRA strategy is tested, while introducing various input data scenarios. The sensitivity analysis method utilised is known as Deterministic Sensitivity Analysis (DSA). DSA is recommended by Parmigiani (2002) particularly in the case of DBBNs. This method proves that PMRA strategy performs efficiently and accurately under different operating conditions. In this context, a detailed sensitivity analysis is performed presenting the level of change in the predicted reliability performance, when there is deviation in the provided input data. The results of this study examine the flexibility in input data deviation, ensuring accuracy in prediction, therefore, safety in operation. The application of PMRA strategy is presented next.

4. Case study

This case study examines the implementation of the PMRA strategy. The present study utilises raw input data such as temperature and pressure gathered from actual ship operational conditions. The demonstrated PMRA raw input case study takes into account systems such as the air supply and cylinders. It is essential to clarify that the entire PMRA strategy development has been taken place in Java programming language as it benefits on cross-platform features, enabling compatibility between different operating systems (i.e. Windows, Macintosh and Linux).

The data has been gathered by the automatically created report of DanaosONE data collection platform. DanaosONE is a Business-to-Business (B2B) gateway to e-servicing for the maritime and oil and gas industries. Similarly, in registering a company into a Business Association, DanaosONE allows access to a maritime-dedicated web and mobile environment of trusted companies Danaos (2015). It is important to highlight that PMRA strategy is developed in acquiring data directly from the automatic DanaosONE platform generated report.

PMRA strategy has been tested through this case study, while collecting input data from a Panamax container ship. The vessel has been equipment with an 8-cylinder 2-stroke slow speed marine diesel engine (MAN B&W 8K90MC-C).

4.1. Air supply system

Major function of the internal combustion engines involves the supply of fresh air and the removal of exhaust gases. This cyclic process is known as gas exchange. The reliability assessment of the involved maintainable units and components involved in both of these functions are considered in the PMRA strategy case study. The separation of the air supply and removal of exhaust gases functions is challenging task because of this cyclic process. Therefore, this reliability assessment introduces two systems, the air supply and the cylinders for examining the systems involved in the fresh air supply function and the removal of the exhaust gases, respectively.

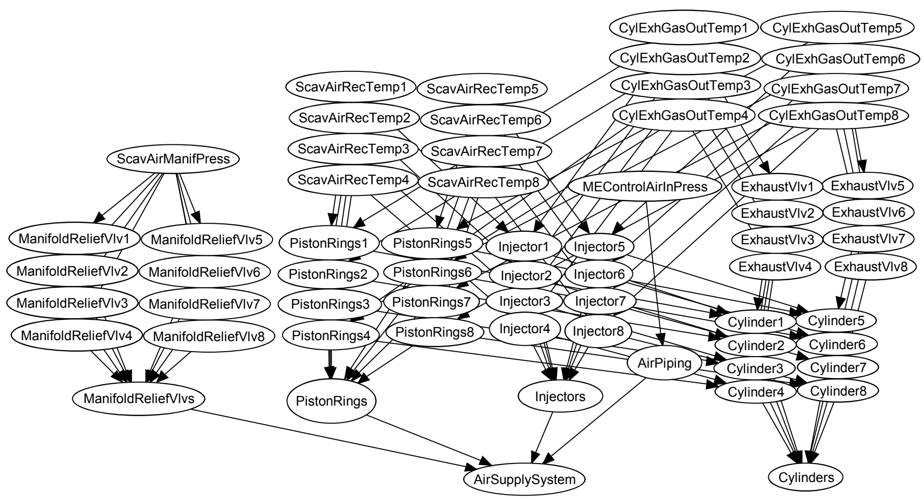

Figure 2: Air supply and cylinders network

However, due to this cyclic process, interdependencies of the input measurements and maintainable units' reliability are required between the air supply and the cylinder systems. This network arrangement allows in a flexible manner the implementation of connecting nodes of different systems as shown in

Figure 2. This technique of interconnections and integration of nodes of various systems produces an overlapping of information among the air supply and the cylinder systems, hence each section supplements the other. The removal of exhaust gases by blowing fresh air is known as scavenging. Modern engines have installed exhaust gas driven Turbochargers (T/C) for scavenging and supercharging processes (i.e. removal of exhaust gases and supply of fresh air for compression respectively).

Improper scavenging can cause collection of fuel oil in the scavenging space of the engine. Hence, unburned fuel may be blown into the scavenge space due to damaged piston rings, faulty timing or damaged injectors. This faulty incidence can lead to scavenge fire. Therefore, engine power will be reduced diagnosed from higher exhaust gas temperature at the affected cylinders. Further information related to defects, diagnostics and engine inspection and maintenance suggestions due to improper scavenging and increased exhaust gas temperature are discussed at the decision-making stage. These functioning interdependencies are considered through the implementation of the network arrangement.

Table 1: Air supply and cylinder system input requirements

System	Component	Required input
Air Supply	Piston rings	Scavenging air receiver temperature/cyl.
		Cylinder exhaust gas outlet temperature/cyl.
	Manifold relief valves	Scavenging air manifold pressure
	Injectors	Scavenging air receiver temperature/cyl.
		Cylinder exhaust gas outlet temperature/cyl.
	Air piping	M/E control air inlet pressure
Cylinders	Exhaust valves	Cylinder exhaust gas outlet temperature/cyl.
	Cylinder 1-8	Injector 1-8
		Piston ring 1-8
		Exhaust valve 1-8

Overall, the air supply system consists of subsystems, components and specific input data measurements, which are denoted in Figure 2 as nodes. More specifically, piston rings, manifold relief valves, injectors and the air piping are considered. The reliability assessment of the piston rings is examined in groups of rings per cylinder on the piston. Therefore, eight nodes are demonstrated in Figure 2 due to the eight cylinder engine installed on the vessel. Similar node arrangement has been been considered for the eight injectors and manifold relief valves. Table 1 presents the input data requirements of the air supply system and the cylinders and the incorporated components.

4.2. Cylinders

The second system involved in the PMRA strategy case study is the cylinder. This network part collaborates with the air supply system, where both manage the required fresh air supply and the scavenging. Analytical description of this cyclic process is provided in the air supply system section above. The utilised engine is the MAN B&W 8K90MC-C, hence eight cylinders are arranged in this study and reliability network arrangement as shown in Figure 2. The network of the cylinders has examined on the level of each cylinder as unit and shown as separate node. Each cylinder has direct connection with the respective injector, piston ring group and exhaust valve, accordingly, indirect connection with the measurements of scavenging air receiver temperature per cylinder, and the cylinder exhaust gas outlet temperature per cylinder. On the other hand, the exhaust valves have direct connection with the cylinder exhaust gas outlet temperature. The injectors, piston rings and exhaust valves demonstrate an operating interconnection of units of different subsystems. This is a valuable flexibility of DBBNs that the rest of the risk assessment tools are not suitable.

5. Case study results

In this section, the predicted reliability performance results of the raw input data case study are demonstrated and examined. This application is developed as part of the PMRA strategy implementation by utilising raw input data gathered on-board a container ship, while sailing in actual/real operational conditions. It is essential to clarify in advance that the involved input data is raw recorded within a continuous time-line of almost a month. Therefore, reliability performance predictions are demonstrated by taking into account specific time intervals. The time recorded interval is set as one measurement per operational hour.

More specifically, the acquired results are plotted in half-monthly intervals. The first two points within the arranged time-line of the x-axis denote the reliability performance in regards to the recorded period of time. The first point (at 0.5 position) signifies the recorded reliability performance of cluster 1 as acquired by the data mining method, whereas the second point at 1.0 the second cluster. Overall, both points represent the reliability performance (tendency of deviation) of the first month (recording time). On the other hand, the following points in the time-line (i.e. 1.5 to 3.5 months) signify the acquired predicted reliability performance of the upcoming period of time. Moreover, points 1.5 and 2.0 represent the reliability performance prediction of the following month, 2.5 and 3.0 of the second predicted month and point 3.5 the reliability performance of the first cluster of the third predicted month.

As part of the conditional probability features, each of the considered datasets involves two states such as the working and failing. The working state expresses the reliability value, whereas the failing, the unreliability as shown in Equations 1-4. Additionally, each node presenting system, component or measurement in Figure 2 has equal marginal probability with respect to the others. This decision allows the minimisation of subjective and controversial characteristics on the predictions and the simplicity on sensitivity analysis.

5.1. Results of air supply system

This section demonstrates the results of the PMRA strategy and practical inspection and maintenance suggestions as part of the decision-making stage. Firstly, air supply system consists of piston rings, injectors and manifold relief valves per cylinder and the air piping. Different sources of raw input data are involved in the air supply system such as the scavenging air receiver temperature per cylinder, scavenging air manifold pressure and main engine control air inlet pressure as shown in Figure. 3.

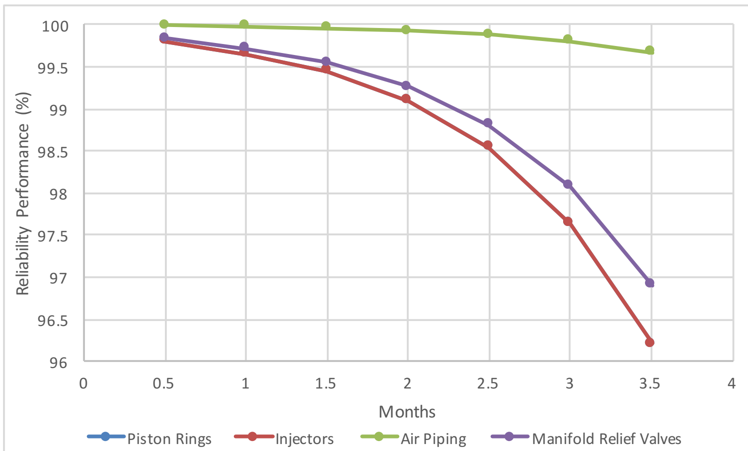

Figure 3: Reliability performance results of air supply system

Another node interconnection is required for the reliability performance assessment of piston rings and injectors by taking into account the cylinder exhaust gas outlet temperature per cylinder in parallel with the scavenging air receiver temperature per cylinder (considering equal marginal probability as described above). More specifically, Figure. 3 presents the reliability performance of piston rings, injectors, air piping and manifold relief valves, while data has been recorded as well as the predicted values of the following two and a half months. Injectors and piston rings obtain the weakest reliability performance, which is initiated at 99.8% and dropped to 96.2%. Uniformity in the current and predicted reliability performance results of these two components has been identified. These results demonstrate similarities in the gathered data sets' statistical characteristics, hence the predicted values as well. These maintainable components are associated with the scavenging air receiver temperature and cylinder exhaust gas outlet temperature. Manifold relief valves present reliable operation from 99.84% to 96.91% while they are linked with the scavenging air manifold pressure. Lastly, air piping is the most reliable maintainable unit reaching figures from 99.99% to 99.67%.

Figure 4 presents the developed Failure Modes and Effects Analysis (FMEA) tool, allowing decision-making, while fulfilling manufacturer's requirements. The FMEA presents practical solutions per system correlated to the appropriate measurement and recorded parameter. Additionally, the FMEA table provides extensive information with respect to potential failure modes, effects of failure, equipment and component affected as well as potential causes.

System	Measurement	Parameter	Failure mode	Effect of failure	Equipment affected	Component affected	Potential cause
Air Supply	Scavenging air receiver	Temperature	Improver scavenging	Loss of power and high exhaust temperature at affected cylinders	Turbocharger	Piston rings, Injectors	Faulty timing, Unburned fuel and carbon
	Scavenging air manifold	Pressure	Air inlet pressure lower than expected	Derating engine /Engine damage / Turbo damaged	Manifold	Air flap, Relief valve	Leak Flow back / Leak Flow interruption
			Overpressure	Engine damage / Turboblower damage	Manifold	Relief valve	No flow
	M/E control spring air	Pressure	Air Leakage	Derating Engine	N/A	Piping Joints	Leak
Cylinders	Exhaust gas outlet	Temperature	Increased Exhaust Gas Temperature		Fuel Injectors Cylinder Air coolers Turbocharger Fuel oil	Piston rings Exhaust valves	Leaking fuel Worn fuel pumps Blow-by, piston rings Leaking exhaust valves Fouled air side Fouled water side Fouling of turbine side Fouling of compressor side Quality of fuel oil

Figure 4: Air supply and cylinders network

It is necessary to clarify that all collected raw input data sets fulfil the safety requirements demonstrating reliable functioning without reaching or exceeding the manufacturer's maximum or alarm levels HYUNDAI-MAN (2010a) and HYUNDAI-MAN (2010b). These levels are presented in Table 2 below. However, the datasets of the collected temperature indices increase the second half of the first (recorded) month, whereas the pressure measurements negligibly dropped. The recorded input data for the entire data gathering time-line as well as the predicted indicate reliable operation without the requirement of introducing inspection or maintenance actions. However, it is essential to continue monitoring the piston rings and injectors by ensuring that the presented reliability drop lies within the acceptable limits.

5.2. Results of cylinders

The final arrangement of maintainable units and components can be assumed as system and it is known as cylinders. PMRA strategy application involves an eight cylinder, 2-stroke marine diesel engine. Therefore, raw input data measurements are collected per involved cylinder. More specifically, cylinders system consists of units such as cylinder 1 to 8. Each of these units integrates input from the particular cylinder exhaust valve, injector and piston rings.

Table 2: Minimum, maximum and alarm levels

Measurement limits	Value
Cylinder exhaust gas outlet temperature (Alarm)	520.0
Cylinder exhaust gas outlet temperature (Minimum)	380.0
Cylinder exhaust gas outlet temperature (Maximum)	500.0
M/E control air inlet pressure (Alarm)	5.5
M/E control air inlet pressure (Minimum)	6.5
M/E control air inlet pressure (Maximum)	7.5
Scavenging air manifold pressure (Minimum)	0.1
Scavenging air receiver temperature (Alarm)	65.0
Scavenging air receiver temperature (Minimum)	25.0
Scavenging air receiver temperature (Maximum)	51.0

Functional and crucial interconnection among different nodes is utilised in the case of cylinders by incorporating input from maintainable units (i.e. piston rings and injectors) of air supply subsystem. This option of flexibly arranging the network and combining input among every required node is gained by the implementation of the DBBNs. In particular, injector and piston rings nodes are associated with scavenging air receiver temperature and cylinder exhaust gas outlet temperature. On the other hand, exhaust valves are connected with the involved cylinder exhaust gas outlet temperature.

As shown in Figure. 5, the reliability performance of cylinder 1 is demonstrated for the involved marine diesel main engine. It is essential to highlight that the acquired results present almost the same reliability performance in the entire timeline, while gathering the raw data as well as in the predicted time

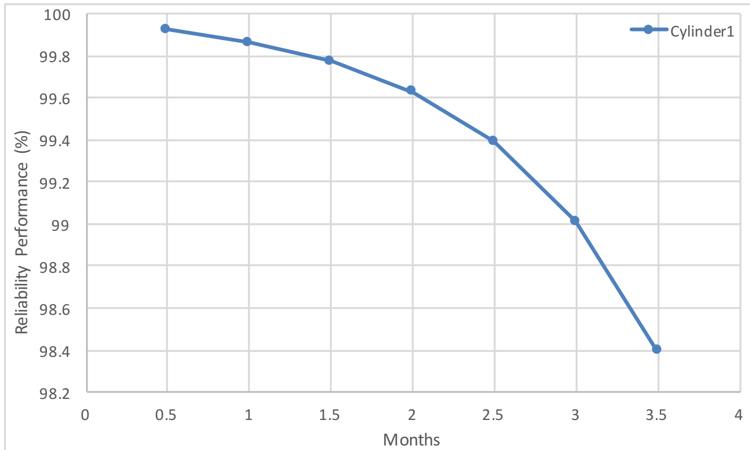

Figure 5: Reliability performance results of cylinder 1 - system level

segment for all involved cylinders. The acquired results show initial reliability performance at 99.92%, which is dropped at 99.86% during the data gathering period of time. In the following predicted timeline, the reliability varies from 99.77% to 98.4%.

The uniformity of the cylinders' results has to be explored further, in order to identify common aspects of the collected data sets. In Figure 6, the exhaust gas outlet temperature per cylinder is provided. More specifically, the average, maximum and deviation figures of temperature data sets per cylinder are presented. The plotted curves declare uniformity in pattern of the data set characteristics. Therefore, each data set per cylinder seems to perform similarly to the remaining as the maximum, average and deviation values denote.

It is worth mentioning that according to the main engine manufacturer manual the maximum acceptable cylinder exhaust gas outlet temperature is at 500 °C, whereas the alarm is set at 520 °C. According to Figure 6, the maximum reached temperature is found on cylinder 8 at 361 °C, which is much lower than the maximum acceptable and the predefined alarm. Therefore, the collected data as well as the acquired predictions lead to slow steaming operation in order to reduce fuel consumption and the sailing speed (approximately service speed is at 18 knots).

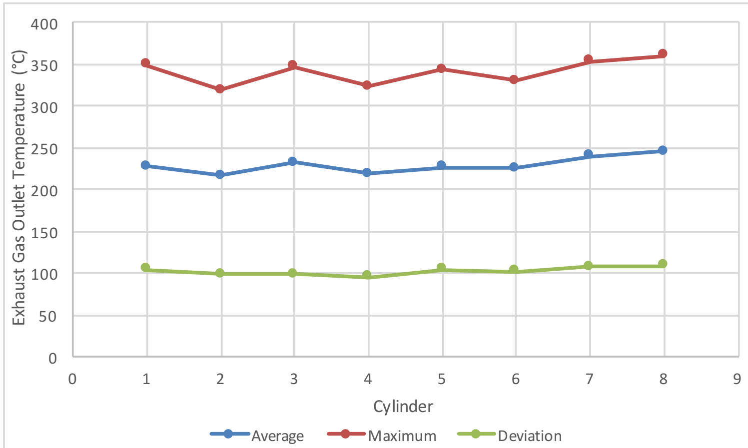

Figure 6: Cylinder exhaust gas outlet temperature raw data records

On the other hand, Figure 7 demonstrates the recorded and predicted reliability performance of cylinder 1 on component level. More specifically, in Figure 6, piston ring 1, injector 1 and exhaust valve 1 are plotted respectively. The uniformity of results regarding the piston ring 1 and injector 1 has been examined and explained above as it has direct relation to the recorded input data.

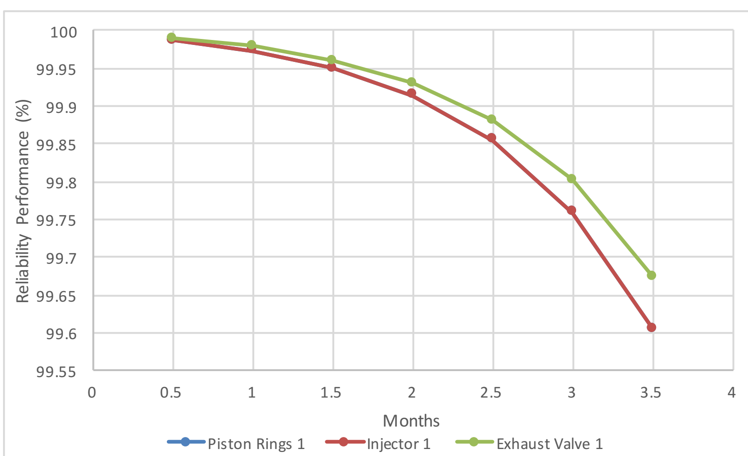

Figure 7: Reliability performance of Cylinder 1 component level

6. Sensitivity Analysis (SA)

Overall, PMRA strategy has been tested on different ship systems. These ship machinery and equipment take into account a complex structure incorporating various nodes which denote many subsystems, maintainable units and components and associations among them. This complex structure makes SA a challenging task. Therefore, the implemented SA has to be performed on a particular component or maintainable unit, which will allow efficient and effective testing enabling the input data adjustments as required and will be demonstrated next.

An essential component for achieving the ship sailing functioning is the thrust bearing, which permits rotation between parts, while they are designed to support predominately axial load. The thrust bearing (also thrust block) is placed right after the ship Main Engine (M/E) and transfers the thrust from the propeller to the hull of the ship. Therefore, it has to be solidly manufactured, assembled and mounted on a solid frame to perform its task by withstanding normal and shock loads. According to HYUNDAI-MAN (2010b), due to the friction in the thrust bearing, the shaft power is approximately 1% less than the effective engine power. Thrust bearings are difficult to dismantle for inspection and maintenance activities, while their improper functioning will lead to wasted power due to friction. Hence, the friction will result in overheating the moving thrust bearing elements.

In this section, an analytical deterministic sensitivity analysis scheme is demonstrated taking into account different operational scenarios. The entire approach considers the raw data as baseline of further assessment. Moreover, the developed scenario analysis is applied by adjusting the raw data set simulating actual operational conditions that may lead to failure or malfunctioning of the thrust bearing.

6.1. Assessment of gradual temperature increase

In order to examine various operational scenarios while controlling uncertainty and adjusting appropriately the raw data set, a specific data modification plan has to be introduced. This SA scheme employs the actual raw data set of the thrust bearing, which is named real-data (i.e. refers to initial ship measurements). The real-data is incremented by 10% in each iteration until the forecasted results illustrate a fully unreliable state (reaching almost 0% predicted reliability performance).

First of all, it is essential to highlight that various testing and verification iterations have been carried out of increasing increments at 1% and 5%. Hence, it has been noticed that in these cases, the reliability performance predictions have not been affected, therefore no failures or malfunctions have been identified. More specifically, in cases of increment 1% and 5%, there is no deviation in the acquired predicted results. This stable predicted state confirms reliable operating condition of the thrust bearing, because real-data are a lot lower than the defined alarm/warning point. According to the testing cases undertaken, the following decided plan involves scenarios of real-data increase by +10%. This attempt intends to examine the input data deviation associated with the acquired predictions. The implemented Deterministic Sensitivity Analysis (DSA) cases are listed in Table. 3 below and performed for reasons that will be explained analytically in this section.

As shown in Table. 3, seventeen DSA cases have been introduced for testing the predictive reliability performance of PMRA strategy and the methodology itself. Initially, it is important to clarify that the timeline has been divided into three state sections (segments). The first one involves the first month of data gathering, the second segment the first predicted month and the third section the second predicted month. These segments of time will be used to define the remarks of Table. 3.

Stable performance. This description refers to the performance (current and predicted), which has been obtained identically the same for all involved DSA cases. Minor reliability drop is assumed as stable performance (i.e. from 100% to 99.88%). It has been identified only in fully reliable state cases (reliable states in current and predicted timeline).

Table 3: Cases of implemented Deterministic Sensitivity Analysis (DSA)

No	DSA Case	Result Description/Remarks
1	real data (reference point)	collected onboard, reliable state
2	real +10%	stable performance, reliable state
3	real +20%	stable performance, reliable state
4	real +30%	stable performance, reliable state
5	real +40%	stable performance, reliable state
6	real +50%	minor deviation, reliable state
8	real +52%	partially unreliable state
9	real +53%	partially unreliable state
10	real +54%	excessive unreliable state
11	real +55%	excessive unreliable state
12	real +56%	fully unreliable state
13	real +57%	fully unreliable state
14	real +58%	fully unreliable state
15	real +59%	fully unreliable state
16	real +60%	fully unreliable state
17	real +61%	fully unreliable state

Reliable state. It denotes the reliability performance, which has been acceptable (below threshold) for the entire timeline. In other words, no failures or malfunctions are obtained or predicted.

Minor deviation. A negligible reliability drop has been identified, compared to previous cases (below threshold, small deviation).

Partially unreliable state. This state denotes to both existing and forecasted states. Partially unreliable means that degradation and unreliable figures have been acquired in the predicted timeline only. The higher the temperature increase the faster the reliability drop.

Excessive unreliable state. The entire predicted timeline has been within the unreliable range, below the alarm/warning threshold.

Fully unreliable state. This state describes entirely unreliable performance for both existing and forecasted timeline sections. In other words, failure measurements have been recorded in the data collection period of time. More specifically in Figure 8, the reliability performance of the thrust bearing is demonstrated in increasing intervals of 10% up to 61%.

The real-data refers to the initial data set as collected onboard, while the ship was sailing. This data set consists of indices i, which in total are 696 (measurement/data points). This process involves the escalation by the particular percentage of each recorded data point (i: index) within the overall data set (origin of real-data).

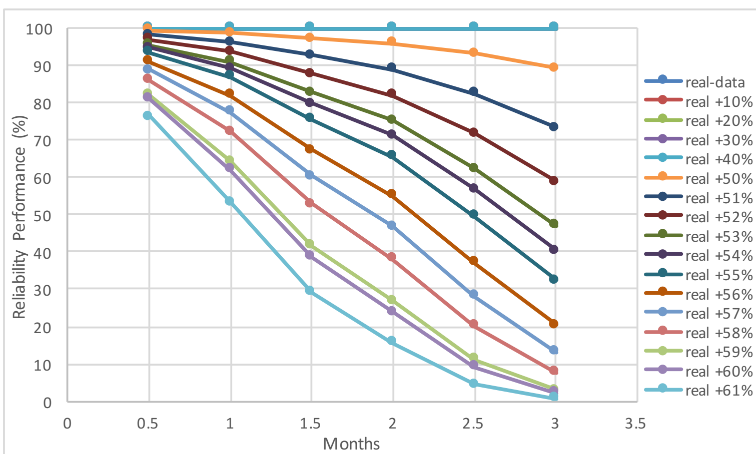

Figure 8: Incremental scenario analysis of thrust bearing

As shown in Figure 8, the thrust bearing presents identical reliability performance utilising the real-data as well as in the cases of 10% up to 40%. This similarity in the acquired results occurs due to low operational thrust bearing lube oil outlet temperature, which leads to reliable predictions. On the other hand, negligible deviation of the obtained results is presented in the case of 50%, where 10% reliability drop is forecasted at the end of the second predicted month of functioning. At this state, it is essential to highlight that 10% reliability drop in actual operational conditions is not minor decrease. The DSA plan involves 10% increment of the real-data, it has been noticed 87% reliability drop from real-data +50% to real-data +60%.

On the other hand, deviation of the obtained results is presented in the case of 50% as shown in Figure 8, where 10% reliability drop is forecasted at the end of the second predicted month of functioning. The following level of sensitivity investigation involves increase at 60% of the existing real data. In this case, the reliability drop is immediate, which starts at 80.9% and decreases down to 2.19%. Due to this excessive reliability drop, further SA investigation has been carried out in intervals of 1%, between the cases of 50% and 60%. This detailed assessment explores the reliability drop and PMRA strategy performance in gradual sensitive (as it is narrowed at 1%) real-data increase.

The examined DSA cases of real +51% to +53% demonstrate a gradual reliability drop, where unreliable input data have not been utilised yet. However, experimentally it has been confirmed that reliability performance below 80% incorporates unreliable data. This statement of the reliability threshold will be clarified in case the analytical discussion of real +56% next. Therefore, case real +51% is the first scenario, which associates unreliable prediction in the third month (73.26%). Gradually, this reliability drop to unhealthy states has been transferred to earlier predicted points in the timeline. More specifically, real +52% presents the second forecasted month to be unreliable as in real +53% case as well.

In cases such as real +54% and real +55%, excessive unreliable state has been identified. As defined above, the entire predicted period of time has been in unreliable state. However, the data collection time (months 0.5 and 1) consists of reliable measurement below the warning threshold.

In Figure 8, the cases of real-data +56% up to 61% have been shown as well. It is essential to clarify that real +56% is the first examined scenario, which involves in the recorded input data unreliable measurements. More specifically, 22 out of 696 (total size of data set) unreliable measurements have been incorporated by increasing the real-data. The first two reliability processed points at plotted positions 0.5 and 1 reach 90.9% and 81.86% respectively. These two points denote the reliability performance of real-data, while it is increased by 56% for the first month of the data gathering period. As long as real-data +56% is the first data set, which includes unhealthy points, performance at 90.9% and 81.86% (which is not predicted yet) defines the percentage threshold at almost 80%. In other words, reliability performance lower than 80% ensures recorded data points at 90 °C or higher.

More analytically, the major reliability drop, in cases where the current data are unreliable as well, has been identified in cases real-data +56% to +61%. The number of data points (in the data collection time) above the warning level at 90 °C have been presented for the cases real-data +56% to +61%.

7. Concluding remarks

The present research has elaborated on the subject of predictive reliability assessment of inspection and maintenance in the maritime transportation mode. The proposed Probabilistic Machinery Reliability Assessment (PMRA) strategy is established by introducing the employed data analysis algorithm and reliability assessment tool. At first, the data mining method of k-means takes place allowing to extract information from a data set and transform it into an understandable structure for further use. The development of PMRA strategy takes place on different levels initiated by introducing the principle aspects of the suggested strategy. The model development continues by selecting the appropriate methods and tools leading to the overall establishment and proposal of PMRA strategy.

PMRA strategy achieves reliability performance assessment of ship machinery and equipment beyond diagnostics by establishing prognostic reliability state modelling. The suggested strategy recommends an individual methodology for inspection and maintenance of ship machinery and equipment. PMRA strategy integrates the assessment of the reliability performance of various onboard installed machinery and equipment provided by different manufacturers and suppliers. Therefore, this is a novel solution to combine and process information from various systems targeting a holistic view of the reliability and safety on board the ship.

Summarising, the key finding of this predictive reliability assessment study and the implemented sensitivity analysis scenario scheme confirm that PMRA strategy is capable of processing reliability performance predictions by considering raw data. Furthermore, DSA proves the capability of PMRA strategy to process successfully various data sets incorporating healthy and unhealthy data points. The suggested DSA approach verifies the PMRA strategy in processing data sets, while confirming degradation of the reliability performance in increasing intervals of 1% and 10% of the involved temperature measurements. On the other hand, according to existing real-data and the DSA scheme performed, temperature increase up to +50% indicates reliable and non-sensitive operation for the entire predicted period of time.

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This statement is signed by all the authors to indicate agreement that the above information is true and correct (*a photocopy of this form may be used if there are more than 10 authors*):

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